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Symmetry Based Multi-modality Registration of the Brain Imagery

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Abstract- *We propose a framework of multi-modality brain registration methods using symmetry plane as the principal feature for geometric matching. By bringing the symmetry plane of two rigid objects into coincidence, we can potentially match two objects approximately if there is no apparent elastic distortion. We illustrated this concept using Visible Human dataset, that included color cryosection, and radiological data, from which we extracted 3D mesh models of skin, brain and skull, and aligned them into nested bodies. Each model was generated with different spatial orientation and resolution, and their alignment, was guided by the underlying anatomical relationships in the head region, and a requirement, by an application that the meshes didn't intersect. After alignment of the symmetry planes, obtained for each mesh using spatial affine transformations, the further geometric adjustment, to achieve complete registration of the nested models, is confined within a 2D plane (i.e. the symmetry plane). This simple method of registration of mesh anatomical models, has a potential to significantly reduce the degrees of freedom in various 3D brain registration applications. It can be also treated as a pre-registration operation before applying other registration methods.*

Keywords- *Brain symmetry, Principle Component Analysis, 3D symmetry, Registration, Non-rigid,*

1. INTRODUCTION

Computer aided clinical diagnosis and therapy planning often makes use of patient-specific information derived from multiple imaging modalities. Each modality potentially provides complementary structural information about the anatomical region of interest.

In the past decades, multi-modality image registration produced a substantial body of research and publications. A diversity of methodologies [1] have been developed, that can be categorized according to different: 1) type of features used for registration (i.e. intensity based vs. feature based) 2) type of transformations (rigid vs. non-rigid) and 3) parameter determination (search vs. closed form).

Given that a symmetry plane remains spatially invariant within a rigid body, under a series of affine transformations such as rotation, translation and scaling, we prototype a symmetry-based multi-modality registration paradigm. By bringing the symmetry planes of two rigid objects, that were derived from the same subject, into coincidence, we can potentially match two objects approximately if there is no elastic distortion. Kapouleas [2] proposed a way to use the inter-hemispheric fissure plane in three dimensions for the registration between MR and PET images of the brain. However, the method had limitations because the identification of the symmetry plane was a manual process, that required the users to specify several endpoints within several axial sections.

We propose in this paper a fully automated rigid-registration algorithm, utilizing symmetry plane as the principal matching feature to perform this one-to-one mapping among different structures acquired from different image modalities.

We implemented our algorithms on the mesh data from the Visible Human dataset. The brain and skin structured data were generated from Visible Male cryosection, whereas the skull mesh was produced from Visible Male computed tomography(CT). The application that triggered our project is the visual analysis of head trauma injury [3]where specific, strict requirements have to be satisfied for multi-scale high fidelity biomechanical and physiological modeling of injury to head.

We would like to demonstrate that the symmetry-based multi-modal registration method can reduce the searching space from voxel mapping in 3D space to pixel alignment in 2D plane. The symmetry planes of the meshes are defined as digital 2D objects. The method reduces the number of degrees of freedom in the registration process. It has the potential to achieve higher level of efficiency compared to the traditional landmark based approach. We treat the symmetry plane as a yet another feature that can be extracted from an anatomical structure of interest. In summary, this method, that utilizes knowledge about the brain topology, facilitates registration by avoiding many local extrema introduced through exhaustive search, and by employing the geometric constraints imposed by the symmetry plane.

The paper is organized as follows. In section 2, we describe in detail the methods. The algorithm is discussed in section 3. The conclusions follow, in section 4.

2. METHODS

The idea of symmetry plane registration technique is to use the symmetry plane as the principal feature to geometrically align symmetric head structures. As we know, the normal brain exhibits approximate bilateral symmetry with respect to mid-sagittal plane (MSP). This is a plane that best separates the brain into two mirror hemispheres. By treating those internal structures such as brain, skull and skin, extracted from the volumetric images, as symmetrical rigid objects with uniform mass densities, we infer their anatomical relationships from symmetry as the invariable parameter.

We make use of a technique to automatically identify the symmetry plane and to correct the 3D orientation of volumetric brain images, in a cost effective way that was published in our previous paper [cite (Liu, Imielinska et al. 2006], This 3D based method was used for head extraction from its background in volumetric radiological data, with the principle component analysis [4]. The principle axes are the orthogonal axes about which the moments of inertia are minimized. They are used to characterize rigid bodies by the spatial distribution of their mass. We assume that the plane of symmetry in a body is orthogonal to a principal axis [5]

Given the mesh data extracted from the Visible Male represent a complete head volume, the extracted 3D meshes from skin, skull and brain should assume three distinctive principle axes.

The 3D mesh models are created in their local coordinate system, with correct anatomical ratios. This problem will always arise when multi-modal data is used for modeling anatomy. We have to combine the three models in such a way that: (a)They are registered in the same coordinate system in a "nested" fashion; (b) The successive meshes do not intersect.

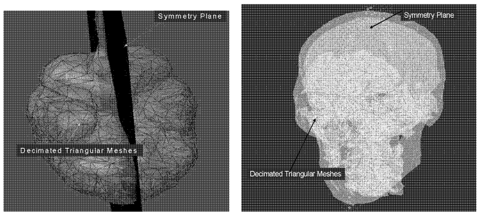
Our algorithm consists of the following operations:

Step 1: Data segmentation and mesh generation;
Step 2: Data decimation;
Step 3: Inter-plane geographic alignment;
Step 4: Intra-plane refinement

Inter-plane geographic alignment will bring objects defined in their local coordinate systems together, making all their corresponding planes of symmetry co-planar. Intra-plane refinement would be a slight rotation of an object defined by rotation of the 2D outline, the intersection of a mesh with its plane of symmetry.

A. Images Used in this Study – Segmentation ,Triangulation and Decimation

For the proof of the concept, we implemented our algorithm using the Visible Human dataset, both color cryosection and radiological data. The meshes for the skin, brain and skull came from a different imaging, segmentation and reconstruction process to be used in simulation of head trauma [3]. We hand segmented the brain from the color cryosection data, to assure the geometric detail of the brain surface. The skin was segmented automatically using simple thresholding algorithm from the color cryosection data. The skull was obtained with hybrid segmentation method [6] from the CT data. The actual meshes were generated with Analyze 7.0 software[7] (Marching Cubes option). The resulting meshes were stored in local coordinate systems and with different scaling factors, but same aspect ratios. We had to bring them together in one coordinate system and make sure that these three meshes did not intersect (a requirement for head trauma simulation) and were correctly registered. We decided to perform registration on the 3D models rather than the volumetric voxel multi-modal data. Hence we had to deal with three very large meshes that had to be pre-processed and made computationally suitable for the alignment process. For example the original meshes contain 464342 vertices and 934716 surfaces. The brain mesh data contains 221593 vertices, and 452464 surfaces. The original skin mesh data contains 287625 vertices and 575496 surfaces. We decimate each very large mesh into a representation with a manageable number of vertices, to make it ready for the symmetry plane computation. We performed the decimation operation by reducing both the number of faces (down to 10%) and the number of vertices (down to 10%). The decimation process did not affect the topological property of each mesh model, but dramatically boosted the computational performance (see Fig.1).



(a) (b)

Fig. 1. (a) 3D mesh data of the brain with its respective symmetry plane; (b) 3D mesh data of the skull, with its respective symmetry plane. Note, that all those meshes have been decimated down to 10% of its original quantity.

B. Symmetry Plane Detection

The decimated object is processed by the algorithm that solves the eigenvalue problem associated with the object's inertia matrix. First, we compute the centroid of the head based on the positions of the vertices. Given the 3D point clouds $P=\{ p_i=(x_i,y_i,z_i) \mid 1 <= i <= m \}$ Let the centroid of the object be represented by $(x_g, y_g, z_g)^T$. The covariance matrix I can be derived from the second-order central moments as follows [8]:

$$I = \begin{bmatrix} I_{xx} & -I_{xy} & -I_{xz} \\ -I_{yx} & I_{yy} & I_{yz} \\ -I_{zx} & -I_{zy} & I_{zz} \end{bmatrix}$$

where

$$I_{yy} = \sum_{x,y,z} [(x-x_g)^2 + (z-z_g)^2]$$
$$I_{xx} = \sum_{x,y,z} [(y-y_g)^2 + (z-z_g)^2]$$
$$I_{zz} = \sum_{x,y,z} [(x-x_g)^2 + (y-y_g)^2]$$
$$I_{xy} = I_{yx} = \sum_{x,y,z} (x-x_g)(y-y_g)$$
$$I_{yz} = I_{zy} = \sum_{x,y,z} (y-y_g)(z-z_g)$$
$$I_{xz} = I_{zx} = \sum_{x,y,z} (x-x_g)(z-z_g)$$

The inertia matrix J can be formed from covariance matrix I, $J=trace(I)I_0-I$ where I_0 is the 3x3 identify matrix. The three eigenvectors of J are the principle axes, which are mutually orthogonal to each other. The centroid and the principal axes completely describe the orientation of a volume given an arbitrary orientation. From our experiments, we found the eigenvector corresponding to the smallest eigenvalue has the direction that is orthogonal to the mid-sagittal plane. Therefore, by computing the angle of this eigenvector with respect to the x, y and z axes, we actually acquire rotational angles (yaw, roll and pitch) of the mid-sagittal plane(MSP). See Fig.2.

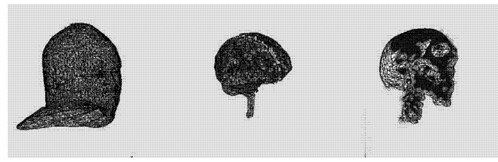


Fig. 2. 3D mesh models of skin, skull and brain, with computed planes of symmetry, respectively.

C. Inter-plane Alignment

In this application, we use principle component analysis to identify our symmetry planes, therefore, we are essentially matching the eigenvectors extracted from the inertia matrix. In our dataset, we obtain the three eigenvectors:$\varepsilon_{\text{Skin}}$=(0.9985,0.0418,-0.0359),$\varepsilon_{\text{Skull}}$ =(0.9998,0.0166,-0.0148),$\varepsilon_{\text{Brain}}$ =(0.9979, 0.0135, -0.0636). We then produce a transformation matrix to map the $\varepsilon_{\text{Skin}}$ to the $\varepsilon_{\text{Skull}}$, using the latter as our reference plane. Likewise, we match the $\varepsilon_{\text{Brain}}$ to the $\varepsilon_{\text{Skull}}$.

Translation and rotation are linear transformations. The space of rotation and translation matrices has degrees of freedom of 3 respectively. In total, six parameters are required to register two rigid bodies (given there is no scaling factor).

We first perform translation. Let T represent the translation matrix.

$$T=\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ \sigma x & \sigma y & \sigma z & 1 \end{bmatrix}$$

where $\sigma x, \sigma y, \sigma z$ are the offset from one center of mass to another center of mass.

Then, we rotate the skin meshes until its MSP comes in plane with the MSP of the skull. The MSP of each model is uniquely characterized by one centroid point and a normal vector that is perpendicular to the symmetry plane. Those normal vectors are their respective smallest eigenvectors that were obtained via previous PCA (principle component analysis) step. We denote the smallest eigenvector of the skin model to be $\varepsilon_{\text{Skin}}=(x_K, y_K, z_K)^T$, and that of the skull model to be $\varepsilon_{\text{SKull}}=(x_U, y_U, z_U)^T$. To rotate the symmetry plane of the skin to match the symmetry plane of the skull, there are two rotational angles, azimuth angle (β) and elevation angle (γ), to perform the rotation operation. The azimuth angle β can be expressed as :

$\beta = \arctan(z_U / (x_U^2 + y_U^2) - \arctan(z_K / (x_K^2 + y_K^2)$

, and the roll angle γ is given by

$\gamma = \arctan(y_U / x_U) - \arctan(y_K / x_K)$

Affine spatial transformation for symmetry planes alignment is then performed. The computed β=-0.0211 γ= -0.0252; Likewise, when we register the brain to the skull, we can obtain the β'=-0.0488, γ'= -0.0031;

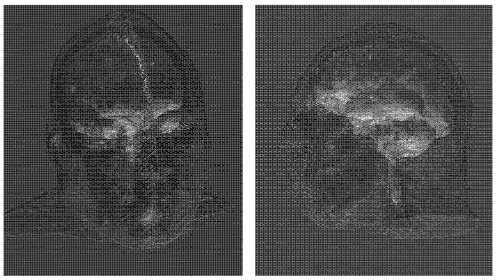


Fig. 3. The registered three mesh data from skin, skull and brain. The MSP intersecting with the meshes are highlighted with scattering points in this diagram $P_{SYM.}/Q_{SYM}$

let $R=R_\alpha R_\beta$ represent the rotation matrix

$R_\alpha R_\beta$=

$$\begin{bmatrix} \cos(\alpha) & \sin(\alpha) & 0 \\ -\sin(\alpha) & \cos(\alpha) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos(\beta) & 0 & -\sin(\beta) \\ 0 & 1 & 0 \\ \sin(\beta) & 0 & \cos(\beta) \end{bmatrix}$$

The rigid transformation is then performed based on the orientation of the symmetry planes. $V_c=V_t \times R \times T$ where V_t is the original skin mesh. V_c is the 3D symmetry plane registered mesh data. The output of this computation makes the MSP of the skin and brain in line with the MSP of the skull (See. Fig.3).

D. Intra-plane Refinement

The matching of symmetry planes involves two rotations and three translations. Therefore, the remainder of the registration only requires one degree of freedom, i.e. intra-plane rotation.

Intra-plane refinement of the registration is conducted within the middle sagittal plane. For each MSP we compute vertices in the corresponding mesh that are close enough (with selected epsilon) to the plane, and those marked vertices, will be used to compute approximation of the intersection of the MSP with its mesh. We digitize the MSP evenly over the three dimensional space (think about it as pixel filled plane) and we identify and "paint" pixels on the MSP that are close to the marked vertices in the previous step. This simple algorithm saves us from a much complex computation of exact intersection of MSP with its mesh. We let $P_{SYM}=\{p1, p2, ..., p_m\}$ and $Q_{SYM}=\{q1, q2, ..., q_n\}$ represent the painted pixels from MSP that are sufficiently close to the mesh vertices. Therefore, P_{SYM} and Q_{SYM} are on their respective MSP planes.

We identify the center of mass for P_{SYM} and Q_{SYM}, before performing the re- parameterization for each point cloud. By changing the vector base from three dimensions to two dimensions, based upon the fact that surface points are aligned in the plane, we obtain a new 2D coordinates u and v, where each element in P_{SYM} and Q_{SYM}, can be represented as $p_i(u_i, v_i)$ and $q_i(u_j, v_j)$.

The subtask here is to seek the best matches between two point clouds, $P_{SYM.}$, and Q_{SYM} , in two dimensions. The similarity measure between the rotated $\{p_i\}$ and fixed $\{q_i\}$ needs to be evaluated. In order to simplify this problem, that is an optimization problem in nature, we propose a way to tackle the problem by first changing the coordinate system from Cartesian space to polar space.

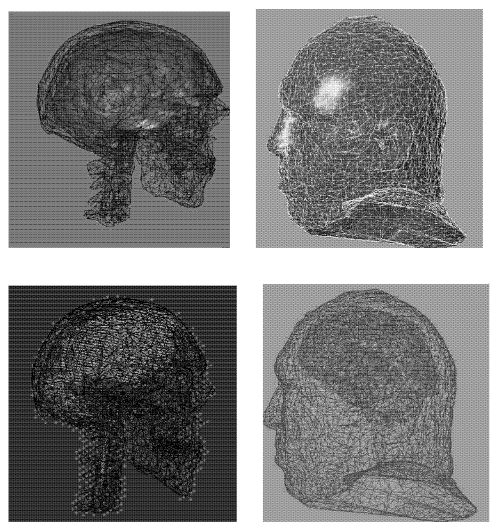


Fig. 4. 3D mesh models of skin, skull and brain, registered using alignment that is guided by the plane of symmetry.

The one-to-one mapping of each point from u-v space to r-θ space, gives rise to a new set $p_i(r,\theta)$ and $q_i(r,\theta)$, where the origin (0,0) in polar coordinates corresponds to the centroid in the Cartesian coordinates.

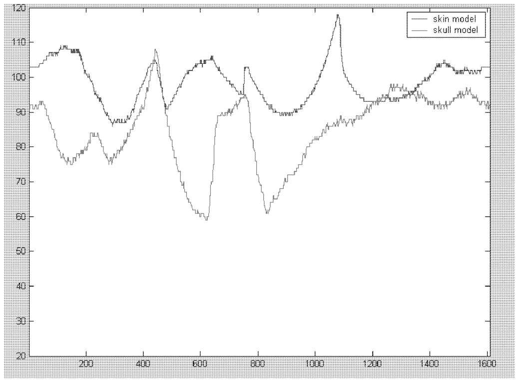


Fig. 5. The profile of P_{SYM} and Q_{SYM} in the polar representation. The vertical axis represents the radius r, of a given surface point toward the centroid. The horizontal axis depicts the rotational angle θ, of a given surface point with respect to a reference line.

In the polar representation, to determine best match, we seek the φ (angle) value that minimizes the mean square error (MSE) between two re-parameterized curve $p_i(r,\theta)$ *and* $q_i(r,\theta)$, spanning the width of 2π. (see Fig.5). MSE is

$$\varepsilon(a) = \sum_{i=1}^{m} d^2(\kappa \cdot q_i(r,\theta), p_i(r,\theta))$$

defined as follows:

, where κ is the rotation matrix. In polar representation, rotation operation is simplified because it is equivalent to a shift along the horizontal axis that depicts the rotational angles of each surface point with respect to a reference line. (vertical axis demonstrates the radii of each point from the centroid).

$$\varphi = a(\kappa) = \arg\max \varepsilon$$

We thus arrive at the angle φ that determines inter-plane rotation of one object for the sake of matching another object. By far, three translations and three rotations have been completely operated on the 3D mesh data, and the final segmentation results can be found in Fig.4.

3. DISCUSSION

A method of 3D multi-modality registration of the brain has been presented. The main advantage of using symmetry plane as the principle feature to perform the geometric transformation, is to reduce a three dimensional problem into a two dimensional one and hence avoid many local extrema in the searching process.

A drawback of our method is that the registration accuracy depends on the accuracy of the symmetry plane detection. Yet in practice we can minimize this error by adopting application-dependent symmetry plane detection algorithms. Principle Component Analysis (PCA) has the computational advantage due to its linearity. While working well for processing of the Visible Human mesh dataset here, PCA method, has the known deficiencies in handling incomplete dataset. For instance, when the radiological data is truncated or includes neck or shoulder, the assumption that the head is ellipsoid-like 3D object is not met and the technique may fail. Of course, a preprocessing could be applied to remove the non-ellipsoid parts of anatomy or supplement the missing ones, but this is out of scope for this paper. One alternative would be to use partial surface matching algorithm to find the best matching surface cloud in order to determine the orientation of the symmetry plane, as proposed in our early work[9]. However, the overhead of identifying the symmetry plane can be very high; e.g., some correlation based symmetry plane detection methods are computationally expensive. Therefore, the selection of symmetry detection methods should consider the trade-off between accuracy and efficiency.

We implemented a simple method to facilitate intra-plane adjustment, assuming there is no elastic distortion between target and source objects. In realistic neuroimages , it is highly likely that an operation of intra-patient registration involves non-rigid transformation. In those scenarios, we can either treat the symmetry plane alignment as a stand-alone rigid registration process, or combine it with more advanced registration techniques such as mutual information[10] registration, with our method playing a role of a preprocessing in a registration hybrid scenario. In the latter case, symmetry plane alignment, will serve as a pre-registration operation by reducing the search space.

Lastly, in some cases, intra-plane adjustment will require in addition to rotation , the uniform scaling (we assume that the segmentation and reconstruction process preserved the aspect ratio of the structures coming from the same subject), to facilitate successful separation of two meshed. This can be easily done by adding scaling component to the MSE equation in section 2.4.

To verify the outcome of our method, we may want to add two more orthogonal planes to compare nested alignment of the intersections of the ,meshes/structures with the planes. Ideally, one would like to show that intersections of the three registered meshes/models with a plane of any orientation will confirm the alignment computed on the original plane of symmetry. We claim that our method provides a good approximation of the desired registration that is constrained, in practice, by the specificity of an application.

4. CONCLUSION

A multi-modality brain registration method, using symmetry plane as the principal feature for brain images geometric matching is presented. By bringing the symmetry planes of two rigid objects into coincidence, we can approximately match two objects if there is no non-linear distortion. We illustrated this concept using 3D mesh models of head structures from the Visible Human dataset. For the extracted 3D meshes of the skin, brain and skull, we computed symmetry plane, for each structure using principle component analysis. We showed that after the reorientation of the models via symmetry plane alignment, using affine spatial transformations: translation and rotation, further adjustment has been confined within 2D plane for intra-plane adjustment. This method, applied to inter-modality registration, has a great potential of reducing the searching space by reducing the number of degrees of freedom. Our algorithm can be used a stand-alone registration method, as well as a good pre-registration process, facilitating subsequent either rigid or non-rigid registration operations.

REFERENCES

[1]. J. B. Antoine Maintz, M.A.V., *An Overview of Medical Image Registration Methods* in *Imaging Science Department*. 1996, Imaging Center Utrecht.

[2]. Kapouleas, I., et al., *Registration of three-dimensional MR. and PET images of the human brain without markers.* Radiology, 1991. 181: p. 731-739.

[3]. Imielinska, C., A.Przekwas, and X.G. Tan., *Multi-Scale Visual Analysis of Trauma Injury.* J. of Information Visualization, 2006. 5(4): p. 279-289.

[4]. Prima, S., S. Ourselin, and a.N. Ayache, *Computation of the Mid-Sagittal Plane In 3-D Brain Images:*. IEEE transaction on medical imaging, 2002. 21(2).

[5]. Minovic, P., S. Ishikawa, and K. Kato, *Symmetry Identification of a 3-D Object Represented by Octree.* IEEE Transactions on Pattern Analysis and Machine Intelligence, 1993. 15(5): p. 507-514.

[6]. Imielinska, C., et al., *Hybrid Segmentation Methods*, in *Insight into Images: Principles and Practice for Segmentation, Registration, and Image Analysis*. 2004, A.K. Peters.

[7]. Analyze7.0 http://www.analyzedirect.com/Analyze/.

[8]. P.Dhawan, A., *Image registration.* Medical Image Analysis. 2003: John Wiley & Sons.

[9]. Liu, X., et al. *Symmetry Identification Using Partial Surface Matching and Tilt Correction in 3D Brain Images*. in *IEEE 2006 International Conference of the Engineering in Medicine and Biology Society*. 2006. New York.

[10]. Viola, P. and W.M.W. III. *Alignment by maximization of mutual information*. in *International Conference on Computer Vision*. 1995: IEEE Computer Society Press.